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Business intelligence and organizational performance: The role of alignment with business process management

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1. Introduction

The business intelligence (BI) concept is not new and has been applied by many companies and other organizations. Lately, it has become even more popular because it includes concepts like analytics, big data and artificial intelligence that form an integral part of digital transformation, an important concept for business executives in companies of all sizes and industries, also in the public sector. Decision-making based on BI use is valuable for organizations that have the ultimate goal of increasing their organizational performance (Audzeyeva and Hudson, 2016; Olszak, 2016; Teoh et al., 2014; Kiron et al., 2014). Still, studies by Audzeyeva and Hudson (2016), Popovič et al. (2012) and Jaklič et al. (2018) show this promise is only realized when the information provided by BI is readily used to improve decision-making and, in turn, business processes, products, services, innovation, and agility. Accordingly, it is recognized that BI only plays the role of an enabler – facilitating the organization's making of better decisions based on the information (Larson and Chang, 2016). BI therefore seems to have an indirect impact on organizational performance.

Further, BI is often just one of many initiatives aimed at improving organizational performance. Business process management (BPM) is a well-known approach to improving organizational performance by way of improved process performance. The integration of BI into BPM initiatives seems natural since they both share the same main goal. For example, the application of BI to manage cross-functional business processes can increase the effectiveness of BI assets use. However, in practice, both concepts are often implemented by different teams, with insufficient cooperation and thus unaligned initiatives (Krause, 2003; Marjanovic, 2007; Williams, 2008; Dokhanchi and Nazemi, 2015). Moreover, many organizations consider BI as primarily or exclusively an IT implementation project and have yet to embrace the understanding of BI as a business initiative that is the only one able to foster business value (Lukman et al., 2011).

The alignment of a BI initiative and a BPM initiative (hereafter: BI-BPM alignment) implies they both "cooperate and contribute to the realization of firms' goals" (Chadwick et al., 2015). Individual elements of the BI-BPM alignment have been analyzed and referred to by many researchers from both the BI and BPM fields (Zaby and Wilde, 2016). In particular, BI is important for implementing Process Performance Measurement (PPM) (Marjanovic, 2007), regarding which information quality and communication are identified as critical success factors (Blasini and Leist, 2013). Therefore, we wanted to further investigate the role of BI-BPM alignment in achieving improved organizational performance by implementing BI. We believe that proper BI-BPM alignment is a way for BI to create business value.

The remainder of the paper is structured as follows. The introduction is followed by a literature review of BI, then BI-BPM alignment and its connection to organizational performance is analyzed. Next, research propositions are elaborated, the research methodology is presented and the research instrument is described. The third part of the paper focuses on the data analysis by employing a survey design and structural equation modeling, followed by a discussion of the results and the conclusion.

2. Literature review and development of the research propositions

This section outlines a brief literature review of a research field and explains how the research model was developed.

Business Intelligence and organizational performance

Although the business intelligence (BI) concept is not new, it is discussed differently by researchers and thus various definitions can be found in the literature (Olszak and Ziemba, 2012; Olszak, 2016, Lukman et al., 2011). This study understands BI as a managerial tool, encompassing the collection of applications, technologies, and processes deployed across companies to help business users address challenges and opportunities, monitor organizational performance, and make better decisions (Lonnqvist and Pirttimaki, 2006; Watson, 2009; Chen and Siau, 2012). BI systems support decision-makers through internal and external data collection, analysis and reporting. Different disciplines affect BI; some contribute to BI from a technical perspective while others are focused on the knowledge search and integration perspective (Ghaida, 2018).

The level of an organization's BI implementation can be determined by considering BI maturity. Generally, a maturity level represents an organization's "capabilities as regards a specific class of objects and application domain" (Röglinger et al., 2012). Raber et al. (2013) believe the benefits achieved from BI are significantly correlated with the BI maturity of an organization. While the list of BI maturity models became quite long over time (Olszak, 2016; Pejić Bach et al., 2018), the models and their usage are quite similar. Most are general BI maturity models that, regardless of organization size or industry type, serve as both a tool for assessing the level of BI implementation and as a roadmap. Maturity models aim to help practitioners successfully deploy BI initiatives within their organizations and reach the desired state of maturity (Chuah and Wong, 2011; Brooks et al., 2015, Harison, 2012). Typically, 4–6 levels of maturity are recognized and the assessment includes certain key dimensions (e.g. IT, data integration and information quality, output quality, measurement).

The analysis of the relatively large number of papers that review the existing BI maturity models led to a list of the most commonly mentioned dimensions, namely: strategic alignment and vision, management sponsorship and support, organizational culture, change management, people skills, resources, technology, and data quality (Brooks et al., 2015). On the other hand, analysis of dimensions of the BI maturity model shows that topics like costs, organizational structures, process orientation, staff, and strategy are rarely addressed (Lahrmann et al., 2010).

The BI maturity model proposed by Dinter (2012) is selected for this research's purpose since it encompasses organizational factors that are very important for the success of BI initiatives (Pejić Bach et al., 2017; Pejić Bach et al., 2018). Dinter's BI maturity model has a structure with three dimensions (functionality, technology, organizational), which are then further divided into categories with corresponding elements (i.e. design objects) (Dinter, 2012). The

model's power lies in its ability to cover all relevant BI design issues and to allow a differentiated view of the maturity level of BI solutions. The model's organizational dimension includes aspects of organization structure, processes, profitability, and strategy, that refer to the alignment with the organizational dimension of the BPM concept (Dinter, 2012).

Some research has examined the impact of BI maturity on organizational performance. The study by Teoh et al. (2014) examined the predictors and outcomes of BI system implementation for Malaysian manufacturers, with the results showing that BI adoption is positively related to company performance in both the financial and non-financial perspective. Other authors (e.g. (Howson, 2008; Kiron et al., 2014)) also made similar conclusions while taking other related factors into account. Moreover, the findings of a study by Chen and Nath (2018) reveal that BI maturity positively influences overall BI success, but also shows that larger organizations have a higher level of BI maturity and success than small and medium organizations. The results of research by Pejić Bach et al. (2018) demonstrate that 'top-performing' organizations are more 'BI mature' than lower performers, while some organizational culture characteristics increase the BI maturity level.

Although we believe the impact of BI on organizational performance is indirect and mediated by the BI-BPM alignment, in order to test whether such impact is fully or partially mediated, a hypothesis is suggested to test the direct impact of BI on organizational performance.

H_1: Business intelligence maturity positively influences organizational performance

The alignment of Business Intelligence and Business Process Management and organizational performance

BPM may be defined as a management approach for improving the performance of business processes (Dumas et al., 2013; Hammer, 2015). While BPM is a holistic and multidimensional concept, organizations most frequently rely on it "in order to achieve continuous process improvement, such as better performance and conformance of their processes" (Malinova et al., 2014). It is often described as a lifecycle entailing: process identification, discovery, analysis, redesign, implementation, and monitoring.

Hinterhuber (1995) argues that business processes can only be managed if they can be measured, yet Hammer and Champy (1993), Burlton (2001) and Hammer (2007) suggest it is important to focus the measurement on processes rather than organizational units. Empirical research results show that process-centered organizational design positively impacts company performance (McCormack and Johnson, 2001; Skrinjar et al., 2008). Accordingly, many studies in the area of BPM stress the need for Process Performance Measurement (PPM) as an essential part of process monitoring so as to assess the current process performance and improve it (Niven, 2002; Kuwaiti, 2004; Smart, 2009; Bosilj Vukšić et al., 2017).

According to Nenadal (2008), "PPM is the monitoring of agreed performance indicators to identify whether a process meets planned targets." Bosilj Vukšić et al. (2013) see PPM as a very important link that connects BPM and BI, but at the same time identify a need to examine what enables this alignment. Bucher et al. (2009) argue in favor of applying BI within BPM, explaining how BI can assist with the execution of the operational process. Moreover, a new term – "process-centric business intelligence" – is defined as the capability of BI to transform business-relevant data into analytic information for the purpose of generating new knowledge for initiating relevant process changes (Bucher et al., 2009). Grossiele et al. (2012) define a

PPM system as an analytical information system that integrates a consistent analysis-oriented database and the use of OLAP techniques.

Thus, BI is not only important to support decision-making within business processes but also for improving business processes (Wanda and Satian, 2015). The results of an extensive literature study by Zaby and Wilde (2017) reveal that the use of BI can assist in the creation of new knowledge to support an optimized business process. Further, some case study analysis shows that BI provides knowledge for certain business processes that can be utilized not only to improve the process efficiency, but can also be part of the exchange of knowledge among all cross-functional business processes and between business departments (Olszak, 2016). Garcia and Pinzon (2017) address: (1) the well-defined business processes and business models; (2) identified the KPIs and established the metrics handled by the business process side; and (3) user-oriented change management as key success factors while implementing BI. Moreover, Williams and Williams (2004) note that “the business value of BI lies in its ability to improve the effectiveness of the core business processes that drive business performance.”

Even though BI’s ability to contribute to an improved business process performance is a strong motivator for adopting it (Ghaida, 2018), organizations still underestimate the capability of BI to initiate efficient decisions for improving the business processes and business performance (Olszak, 2016). BI is often seen as a ‘technical concept’, with little connection to business processes (Marjanovic, 2007), while its strategic role is mainly overlooked (Dokhanchi and Nazemi, 2015). BI projects are usually performed by IT departments and most often carried out independently of corporate strategic and performance management projects (Krause 2003; Williams, 2008). Further, the need to bring BI and BPM initiatives into alignment has been studied by many researchers from both BI and BPM fields (Zaby and Wilde, 2016), yet most authors only describe this concept implicitly and do not give a clear definition. The term "BI-BPM alignment" is hence rarely found in literature, and studies usually focus on a narrow set of that alignment’s elements. In the context of this research, BI-BPM alignment means the two initiatives have an aligned methodology and are coordinated through official communication between the BI and BPM teams. Moreover, it also indicates that BI systems support the performance measurement and management of cross-functional processes.

One of the first to discuss different elements of BI-BPM alignment and its impact on organizational performance was Melchert et al. (2004) who recognized the convergence of BPM and BI, where they see the role of BI as being an enabler of process performance measurement. Smart et al. (2009) also claim that the process performance measurement initiative should be coordinated with the BI initiative within a company. Blasini and Leist (2013) emphasize that information about process performance should be measured and made visible. They also stress the importance of aligning the BI and BPM terminology. The role of process owners, who should possess accurate information about the actual process performance provided by BI systems based on continuously collected data, has been noted by Hammer (2007a), Kohlbacher and Gruenwald (2011), and Kohlbacher and Reijers (2013). In addition, Wieland et al. (2015) argue that control-effective integration of the process performance results within the process structures should be ensured. Moreover, several aspects of PPM are discussed in Hammer (2007a) and Hammer (2007b), including the importance of aligned BI and BPM terminology. These results are further systematized and used in the design of the research instrument (Section 3).

As seen, the need to align the BI initiative with the BPM initiative has already been discussed. Further, BPM could give BI a greater business value and thus propel its implementation from

the technical level to the business level. Much research has confirmed BPM's positive influence on organizational performance, e.g. (McCormack and Johnson, 2001; Škrinjar et al., 2008; Kohlbacher and Gruenwald, 2011; Hernaus et al., 2012). Since PPM is an essential part of mature BPM (Cleven et al., 2011), it is therefore likely that the impact of BI maturity on organizational performance is mediated by the BI-BPM alignment.

Moreover, Jahantigh et al. (2019) developed a conceptual framework for BI critical success factors, which comprises a number of indicators related to process integration, such as standards for the documentation of organizational processes. Their research results indicate that organizations which are more BI mature have also achieved a high level of process integration standards. In addition, qualitative research by Olszak (2016) identified the characteristics of organizations possessing higher levels of BI maturity. The results show that organizations that are more BI mature are strongly oriented toward business processes. They focus on: (1) business processes standardization; (2) implementation of 'fact-based' BPM; and (3) the adoption of a process-oriented culture, learning and the sharing of knowledge. Therefore, organizations with higher BI maturity levels probably have their BI more strongly aligned with their BPM.

The impact of BI-BPM alignment on organizational performance is discussed by Ladeira et al. (2016) who explain that both business process orientation and analytical capabilities affect organizational performance. Similarly, Chen and Nath (2018) suggest that the integration of business analytics into business processes can lead to improvements in organizational performance. Furthermore, Cao and Duan (2017) conclude that greater affinity between the BI and organizational processes can increase the efficiency of data-driven decision-making, thereby positively influencing organizational performance. Hence, it is likely that the alignment of BI and BPM positively affects organizational performance.

For that reason, we formulate the mediating role of BI-BPM alignment in the following way:

> *H2: The impact of BI maturity on Organizational performance is mediated by BI-BPM alignment.*

We can refine that as follows:

> *H2a: BI maturity positively influences BI-BPM alignment.*
> *H2b: BI-BPM alignment positively influences Organizational performance.*

Figure I presents the resulting research model in which BI maturity determines the level of an organization's BI implementation, measured by a modified BI maturity model of Dinter (2012), while organizational performance is represented by dimensions proposed in Law and Ngai (2007), as described below. In the presented research model, we theorize that BI maturity has a direct impact on Organizational performance (H1) and an indirect one through BI-BPM alignment (H2), expecting to show that the impact of BI maturity on Organizational performance is either fully or partially mediated by the BI-BPM alignment, which may be described as the cooperation of BI and BPM in achieving organization's goals. With respect to the mentioned indirect impact, BI maturity affects the BI-BPM alignment (H2a) and the BI-BPM alignment then affects the Organizational performance (H2b), as shown in Figure I.

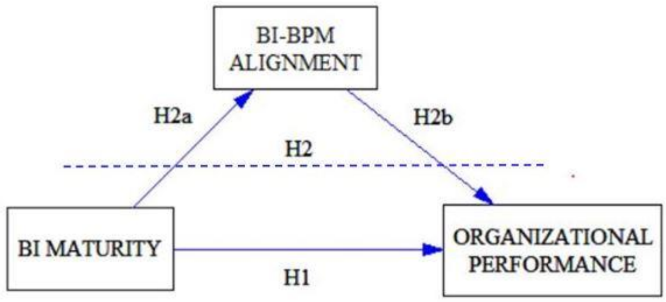

Figure I. Research model of the impact of business intelligence maturity and its alignment with business process management on organizational performance

3. Research methodology

This section describes the methodological approach taken in this study. After reviewing the literature and designing the research model, we selected and adapted the appropriate measurement instruments for the BI maturity and OP constructs (Dinter, 2012; Law and Ngai, 2007). We then developed the BI-BPM alignment construct and its scales following the procedure suggested by MacKenzie et al. (2011). The data collection was followed by a data analysis and interpretation of the results along with a discussion. The main research steps are shown in Figure II.

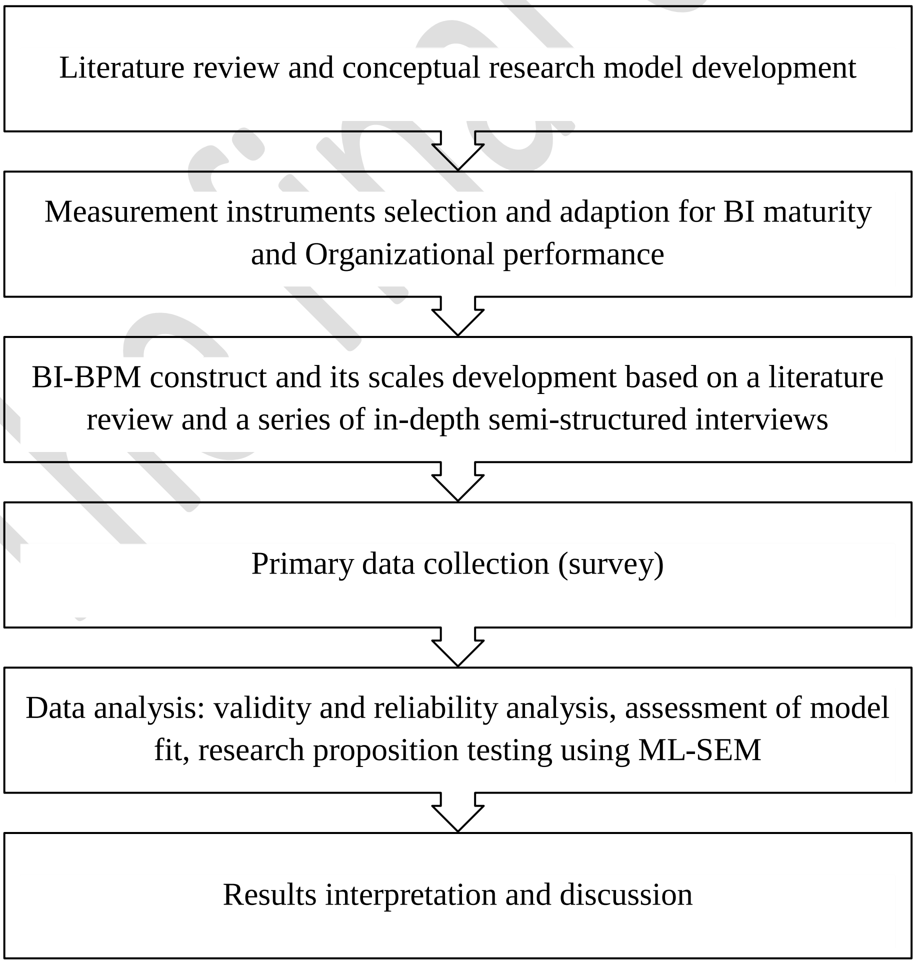

Figure II. Main research steps

Below, we detail the sample used for this research as well as the research instrument and statistical methods used to analyze the collected data.

Sample description

The data on which this research is based were collected in two neighboring countries – Croatia and Slovenia, which were selected for the study due to their common history and similar characteristics, as was also the case in other studies (e.g. Škrinjar et al., 2008, Hernaus et al., 2016). The data collection process had two phases. First, a pilot phase was carried out with the aim to test the developed questionnaire in terms of the clarity of the questions and questionnaire design. During this phase, a series of interviews was conducted, resulting in minor questionnaire modifications. Next, during the main phase of the data gathering, from March to December 2016 questionnaires were distributed to companies operating in Croatia and Slovenia. An invitation to participate in the study was sent in paper form and by electronic mail to members of top management and/or the employees responsible for BI and BPM within a company. The Croatian sample selection frame included the Register of Business Entities that contained a total of 1,765 active medium-sized and large organizations, of which invitations to participate were sent to 500 companies selected for a random sample relying on the method of steps using a table of random numbers. The Slovenian sample selection frame included the business directory bizi.si in which a total of 1,394 active medium-sized and large companies are registered and were included in this research. At the end of the main data gathering phase, a total of 101 responses had been gathered in Croatia (a response rate of 20.2%), while a total of 171 responses had been collected in Slovenia (a response rate of 12.27%). The data were then further examined in order to detect any inconsistencies, outliers and missing values, after which some responses were deleted from the database. Having in mind the research propositions of this study, the final database consisted of a total of 185 responses.

Table I presents details of the sample profile. Out of 185 responses, 70 valid responses (37.84%) were gathered in Croatia, while the rest (115 or 62.16%) were gathered in Slovenia. For the purpose of this research, five sectors of the economy were considered, as described by Gelo and Družić (2015). In that sense, the minority of the companies (1.62%) come from the primary sector, while the majority are from the secondary (37.30%) and tertiary (29.19%) sectors. This roughly corresponds to the actual distribution of the number of companies by industry sector in Croatia and Slovenia combined, i.e. 2%, 32%, 30%, 17 %, and 19%, respectively (Croatian Bureau of Statistics, 2019; Statistical Office of the Republic of Slovenia, 2019), making the sample suitable from this perspective. In terms of the number of employees, the majority of the companies have between 50 and 249 employees (47.03%), whereas the minority are small companies with less than 50 employees (10.81%). Observing the sample from an annual turnover point of view, 37.30% of the companies had an annual turnover of between EUR 10 and EUR 50 million, 30.81% had an annual turnover of more than EUR 50 million, while 22.70% had an annual turnover of less than EUR 10 million.

Table I. Profile of the responding companies

Company characteristics	Sample characteristics	
	No. of companies	Percentage
I. Industry sector		
Primary	3	1.62%
Secondary	69	37.30%

Tertiary	54	29.19%
Quaternary	35	18.92%
Quinary	17	9.19%
no answer	7	3.78%
II. Employee number		
< 50	20	10.81%
50-249	87	47.03%
250-1000	49	26.49%
> 1000	29	15.68%
III. Annual turnover amount		
< 10 mil EUR	42	22.70%
10 mil EUR - 50 mil EUR	69	37.30%
> 50 mil EUR	57	30.81%
no answer	17	9.19%
IV. Country		
Croatia	70	37.84%
Slovenia	115	62.16%

Research instrument

According to the findings of the literature review, the domain of the construct was specified and the research instrument developed. Initially, the questionnaire used for this research was developed as part of a research project. For the purpose of this study, three main parts of the questionnaire are considered and further analyzed; namely: (1) BI maturity measurement; (2) BI-BPM alignment measurement; and (3) organizational performance measurement. Table II presents these constructs along with their associated research indicators and the item descriptions.

BI maturity measurement

Due to the relatively broad focus of the initial research, an aggregated version of Dinter's BI maturity model (Dinter, 2012) was designed. It comprised ten items: (1) the scope of BI systems use; (2) the level of data architecture maturity; (3) the relevance of BI for the organization; (4) the level of technical architecture maturity; (5) the level of data management maturity; (6) the type of BI tools used by the organization; (7) the organizational structure related to BI; (8) the level of BI processes maturity; (9) the level of BI profitability assessment; and (10) the BI strategy. The initial research instrument for measuring BI maturity is presented in Table II. For each stated item, there were two opposite statements – statement A and statement B – one on each side of a 5-point Likert scale. Respondents were asked to state the level of their agreement with either one statement or the other, noting that 1 means strong agreement with statement A, while 5 means strong agreement with statement B. However, for the purpose of this research, only seven items were taken into consideration. Indicators BI2, BI3, and BI9 were excluded from the final model due to the poor loadings that were revealed while performing reliability and validity checks. Following Henseler et al. (2009), items with poor standardized loadings may be omitted if all reliability and validity measures in the final model achieve a significant increase, which is the case in this study. Since this study's purpose is to examine the impact of BI on organizational performance, which can only be realized with the effective use of BI, it is appropriate to exclude those indicators that are used in other parts of the BI value chain (Trieu, 2017). In particular, indicators BI3 and BI9 would already measure such an impact, i.e. "the

competitive process" (Trieu, 2017), in advance. Further, indicator BI2 measures "the BI conversion process" (Trieu, 2017), which results in BI assets and is therefore merely an enabler for the BI-use process.

Table II. Dimensions of BI maturity

ID	DIMENSION	ITEM/STATEMENT A	ITEM/STATEMENT B
BI1	The scope of business intelligence systems use	BI is used in an isolated manner by individuals.	BI is used in all (wherever needed) organizational units, hierarchical levels, and application areas.
BI2	The level of data architecture maturity	Business data management is not addressed in our organization. There are non-existing or heterogeneous semantics.	Internal (both structured and unstructured) and external data are fully integrated, and requirements (e.g. data quality) are met.
BI3	The impact of business intelligence	BI is not considered to have a relevant impact.	Decision-making is based on BI and BI is perceived as having a critical impact on organizational performance.
BI4	The level of technical architecture maturity of BI	No dedicated BI storage is used.	Enterprise-wide data warehouse is used.
BI5	The level of data management maturity	Data integration is manual.	Data integration is automated; dedicated tools for data management and integration are used.
BI6	Type of BI tools used within the organization	We do not use any specific BI tool; manual analysis is performed.	A broad range of BI tools and techniques is used, such as reporting tools, ad hoc analytics (OLAP), in-memory analytics, planning, alerts, forecasts, scorecards, mobile BI, data mining, predictive analytics, and other advanced techniques of analysis and visualization.
BI7	The organizational structure related to BI	There are no specifically defined roles and organizational units for BI.	A BI (business data analytics or similar) competence center with a comprehensive spectrum of tasks and competences exists.
BI8	The level of maturity of BI processes	No explicit processes related to BI are defined.	BI specific processes are defined and actively managed.
BI9	The level of the profitability assessment of BI	There is no profitability assessment of BI.	A cross-project and benefit-oriented profitability assessment of BI takes place.
BI10	The level of BI strategy	No BI strategy exists in our organization.	A dedicated BI strategy exists and clearly reflects the business/IT alignment.

Source: Dinter (2012)

BI-BPM alignment measurement

To develop the BI-BPM alignment construct and its scales, we followed the procedure of MacKenzie et al. (2011). We started with a conceptual definition of our constructs and then

developed, evaluated, and refined the measurement items that represent the construct based on the literature review findings and the interviews with a number of experts and, finally, we assessed the scale validity.

The construct for assessing BI-BPM alignment (PIA) was initially designed by summarizing the aspects presented in the literature review. In particular, it was developed based on aspects shared by organizations that introduce both BPM and BI (Smart et al., 2009; Nieven, 2002; Krause, 2003; Kuwaiti, 2004; Hammer, 2007b; Marjanovic, 2007; Cleven, 2011; Dokhanchi and Nazemi, 2015). The developed construct was additionally tested during the pilot phase of the research through a series of in-depth semi-structured interviews. During these interviews, research groups and experts from various companies included in the pilot phase of the research discussed questions regarding specific alignment indicators (e.g. their importance, what is their current state, what are the gaps, what are the consequences, etc.). Table III presents an overview of the key results of the interviews with experts from selected companies during the pilot phase.

Table III. Main findings of the exploratory research

	Company	Expert	Key results
1.	Provider of different waste treatment services, 400 employees	Chief Process Officer (CPO)	Business processes are well organized and process ownership is established. BI and BPM initiatives are organized in separate departments; yet, they are coordinated through intense communication. BI is used by process owners for process performance measurement based on process-oriented goals.
2.	Insurance company, 2,400 employees	Head of the Organizational Development, HR and BPM Department	BI and BPM initiatives are organized in separate departments, but are coordinated through intense communication, and their terminology is aligned. Process ownership is not established.
3.	Manufacturing company, 2,000 employees	Head of the Strategy Development Department	BI and BPM initiatives are organized in separate departments; process ownership is established only formally. Alignment via the coordination of initiatives, terminology, and the usage of BI for process performance measurement is important, but not yet implemented.

At the end of the pilot phase and after the initial questionnaire was refined according to feedback from the experts during the interviews, the BI-BPM part of the questionnaire had three statements comprising: (1) the coordination of BI-BPM initiatives; (2) the usage of common BI-BPM terminology and the communication of experts from both fields; and (3) the usage of BI systems for measuring the performance of cross-functional processes. For each item, respondents were asked to state the level of their agreement on a 5-point Likert scale, where 1 represented total disagreement with the statement and 5 total agreement with the statement. The dimensions of the BI-BPM alignment and related sources are shown in Table IV.

Table IV. Dimensions of the BI-BPM alignment

ID	DIMENSION	ITEM/STATEMENT	SOURCE
PIA1	BI and BPM coordination	The BPM initiative is coordinated with the BI initiative in our company. Very intensive communication between BPM and BI experts and managers exists.	(Melchert et al., 2004) (Marjanovic, 2007) (Smart et al., 2009) Expert 1 Expert 2

			Expert 3
PIA2	BI and BPM terminology alignment	The terminologies of BPM and BI are aligned. BI and BPM use common terms; a glossary of BI-BPM terms exists.	(Hammer, 2007a) (Hammer, 2007b) (Blasini and Leist, 2013) Expert 2 Expert 3
PIA3	Usage of BI for process performance measurement	BI systems enable the performance measurement and management of cross-functional processes.	(Kohlbacher and Gruenwald, 2011) (Blasini and Leist, 2013) (Kohlbacher and Reijers, 2013) (Wieland et al., 2015) Expert 1 Expert 3

Organizational performance measurement

Organizational performance measurement was performed using the method of self-evaluation as described in Law and Ngai (2007), whose work provides the basis for designing this part of the questionnaire. They defined the relevant aspects based on previous research with the intention to capture not only the financial aspects, but also other non-financial dimensions. It comprised five statements that evaluate the following: (1) level of customer satisfaction with products/services ('value for money'); (2) customer retention rate; (3) sales growth rate; (4) profitability of the organization; and (5) competitive position of the organization. However, the first item which refers to the value for money dimension was excluded from the final model due to poor loading, as was also the case with three items from the BI maturity dimension. In this part of the research instrument, respondents were asked to state the level of their agreement with each statement on a 5-point Likert scale, with 1 denoting total disagreement and 5 total agreement with the statement. The dimensions of organizational performance are shown in Table V.

Table V. Dimensions of organizational performance

ID	DIMENSION	ITEM/STATEMENT
OP1	Value for money	Our customers perceive our products and services as the best in our industry.
OP2	Customer retention rate	Our customer retention rate is high above the average of the industry.
OP3	Sales growth rate	Our sales growth rate is high above the average of the industry.
OP4	Profitability of the company	The profitability of our company is high above the average of the industry.
OP5	Overall competitive position	Our overall competitive position is high above the average of the industry.

Source: Law and Ngai (2007)

Statistical methods

Carious statistical methods were used in the statistical analysis of the collected data. First, discriminant validity and reliability analyses were performed using factor analysis, as well as Cronbach alpha coefficients. Next, the primary data analysis was conducted in terms of descriptive statistics, and the correlation coefficients were calculated. Finally, an assessment of the model fit and testing of the research propositions were conducted using the method of

modeling structural equations relying on the Lisrel software and maximum likelihood estimation method.

4. Data analysis and research findings

This section of the paper summarizes the data analysis process and the research findings.

Validity and reliability analysis

The data analysis process started with discriminant validity and reliability analyses. A factor analysis was performed for the purpose of the validity analysis. The goal of the exploratory factor analysis that was performed was to investigate whether the individual items were similar enough to fit into the same construct, i.e. factor, or, in other words, whether they adequately measure the constructs previously described in the research instrument descriptions. At the same time, exploratory factor analysis checked whether the constructs used are different from each other. Table VI presents a rotated factor matrix for three factors. As seen in Table VI, items BI2, BI3, BI9, and OP1 were omitted from the final model due to weak loadings, as previously explained. The presented rotated matrix is based on items comprising BI, BI-BPM alignment (PIA), and organizational performance (OP) research instrument items.

Table VI. Rotated factor matrix for three factors

Item	Factor		
	1	2	3
BI-1	0.522		
BI-4	0.595		
BI-5	0.726		
BI-6	0.676		
BI-7	0.618		
BI-8	0.699		
BI-10	0.533		
PIA-1		0.850	
PIA-2		0.859	
PIA-3		0.867	
OP-2			0.761
OP-3			0.853
OP-4			0.821
OP-5			0.869

Table VII presents the completely standardized factor loadings along with their t-values and R-squares for the items comprising the BI, BI-BPM alignment (PIA), and organizational performance research instrument. According to Hair et al. (2006), standardized factor loadings should be above a cut-off value of 0.5, with t-values above 1.96. As shown in Table VII, all calculated standardized factor loadings are above the cut-off value of 0.5 and all t-values exceed 1.96, which confirms the validity.

Table VII. Completely standardized factor loadings, t-values and R-squares

Item	Completely standardized factor loading	t-values	R-square	Cronbach's alpha
BI-1	0.952	11.806	0.571	0.782
BI-4	0.864	10.637	0.491	
BI-5	0.814	11.323	0.538	
BI-6	1.010	13.147	0.661	
BI-7	1.016	12.841	0.641	
BI-8	0.930	14.046	0.719	
BI-10	1.047	13.755	0.701	
PIA-1	1.037	-[a]	0.765	0.887
PIA-2	0.933	13.427	0.661	
PIA-3	1.021	14.621	0.747	
OP-2	0.551	-[a]	0.420	0.876
OP-3	0.837	9.352	0.698	
OP-4	0.851	9.372	0.702	
OP-5	0.873	9.613	0.762	

Note: [a] Indicates a fixed parameter in the original solution

Table VII also presents the Cronbach alpha coefficients calculated for the three constructs under observation. As stated in Feldt and Kim (2008), the recommended cut-off value of Cronbach's alpha coefficient should be 0.70 or higher. Therefore, as Table VII shows, all calculated Cronbach alpha coefficients for the observed constructs are above the recommended cut-off value of 0.70. It may therefore be concluded that the reliability is also confirmed.

Primary data analysis

The primary data analysis started with descriptive statistics. Means and standard deviations were calculated. Next, correlation coefficients were calculated for all items of the research instrument used in the model for this study's purpose. Table VIII presents the results for the descriptive statistics and correlation coefficients.

Table VIII. Descriptive statistics and correlation coefficients

	Mean	**σ**	*BI-1*	*BI-4*	*BI-5*	*BI-6*	*BI-7*	*BI-8*	*BI-10*	*PIA-1*	*PIA-2*	*PIA-3*	*OP-2*	*OP-3*	*OP-4*	*OP-5*
BI-1	4.29	0.814	1													
BI-4	4.04	0.877	0.356**	1												
BI-5	3.57	0.998	0.332**	0.251**	1											
BI-6	3.63	1.066	0.312**	0.308**	0.493**	1										
BI-7	4.01	0.866	0.212**	0.336**	0.351**	0.328**	1									
BI-8	3.70	1.040	0.212**	0.265**	0.461**	0.549**	0.390**	1								
BI-10	3.64	0.957	0.286**	0.271**	0.346**	0.316**	0.339**	0.344**	1							
PIA-1	2.96	1.083	0.353**	0.225**	0.390**	0.457**	0.325**	0.403**	0.337**	1						
PIA-2	3.43	1.056	0.306**	0.215**	0.308**	0.465**	0.298**	0.341**	0.334**	0.553**	1					
PIA-3	3.06	1.286	0.254**	0.171*	0.333**	0.401**	0.243**	0.282**	0.304**	0.572**	0.549**	1				
OP-2	3.87	0.850	0.384**	0.241**	0.120	0.132	0.187*	00.091	0.290**	0.325**	0.207**	0.211**	1			
OP-3	3.30	1.002	0.275**	0.208**	0.144	0.277**	0.209**	0.196**	0.344**	0.333**	0.280**	0.345**	0.614**	1		
OP-4	3.29	1.016	0.209**	0.151*	0.186*	0.225**	0.194**	0.211**	0.201**	0.313**	0.270**	0.390**	0.471**	0.696**	1	

OP-5	3.46	1.000	0.270**	0.225**	0.102	0.265**	0.220**	0.199**	0.220**	0.390**	0.346**	0.342**	0.564**	0.708**	0.756**	1

** p-value < 0.01; *<0.05

As may be seen in Table VIII, within the BI group of research indicators the BI-1 research indicator has the highest mean of 4.29 with a standard deviation of 0.814, measuring the scope of BI systems usage within an organization. The lowest mean of 3.57 with a standard deviation of 0.998 was noted for the BI-5 research indicator that measures an organization's level of data management maturity. Within the BI-BPM alignment group of research indicators, the highest mean of 3.43 with a standard deviation of 1.056 was noted for the PIA-2 item, measuring the alignment of the BPM and BI terminology as well as the existence of a glossary of BPM and BI terms. In contrast, the lowest mean of 2.96 with a standard deviation of 1.083 was measured for the PIA-1 item referring to the coordination between BI and BPM initiatives. Finally, for the organizational performance items, the highest mean of 3.87 with a standard deviation of 0.850 was measured for the OP-2 research indicator, referring to the customer retention rate, while the lowest one (mean of 3.29 with a standard deviation of 1.016) was calculated for OP-4, measuring the organization's profitability.

Assessment of the model fit

The assessment of the model fit was performed by calculating fitness indicators. For the purpose of assessing the model fit, chi-square, degrees of freedom, and p-value were calculated, along with a goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), normed-fit index (NFI), non-normed-fit index (NNFI), comparative fit index (CFI), root mean square error of approximation (RMSEA), and 90% confidence interval of RMSEA. The complete list of fit indices, their estimations and explanations for the research model presented herein is given in Table IX.

Table IX. Fit indices for the research model

Fitness indicator	Model estimated	Explanations
Chi-square (χ^2)	153.175	χ^2 is not significant
Degrees of freedom (df)	74	
p-value	0.000	
χ^2/df	2.070	Very good, close to 2.0
GFI	0.833	Good, close to 0.9
AGFI	0.834	Good, close to 0.9
NFI	0.914	Good, close to 0.9
NNFI	0.943	Very good result
CFI	0.953	Very good result
RMSEA	0.076	Good, close to 0.08
90% confidence interval of RMSEA	(0.059–0.093)	Upper limit <0.10, a good result

When considering the recommendations for assessing the model fit (e.g. Hooper et al., 2008) and the calculated values of the fit indices for the presented model, as shown in Table IX, it may be concluded that the model is a good fit.

Testing the research propositions

To test the research propositions, the method of modeling structural equations was employed using the Lisrel software. As proposed by Nunnally (1967) and later widely accepted, the rule of thumb in setting a lower bound of an adequate sample size for conducting a structural

equation modelling analysis is 10 observations per indicator variable. In our case, we have a sample size of 185 companies, which corresponds to the mentioned rule of thumb since there are 14 observed variable indicators, which makes a minimum size sample of 140 observations. Moreover, the minimum sample size for structural equation modeling, as stated in Tinsley and Tinsley (1987), Ding et al. (1995), Tabachnick and Fidell (2001), and Sudigdo et al. (2019), is between 100 and 150, meaning we may conclude that our sample size of 185 is adequate. The result of the research proposition testing is presented in Figure III, showing the path diagram along with the path coefficient estimates and their significance levels.

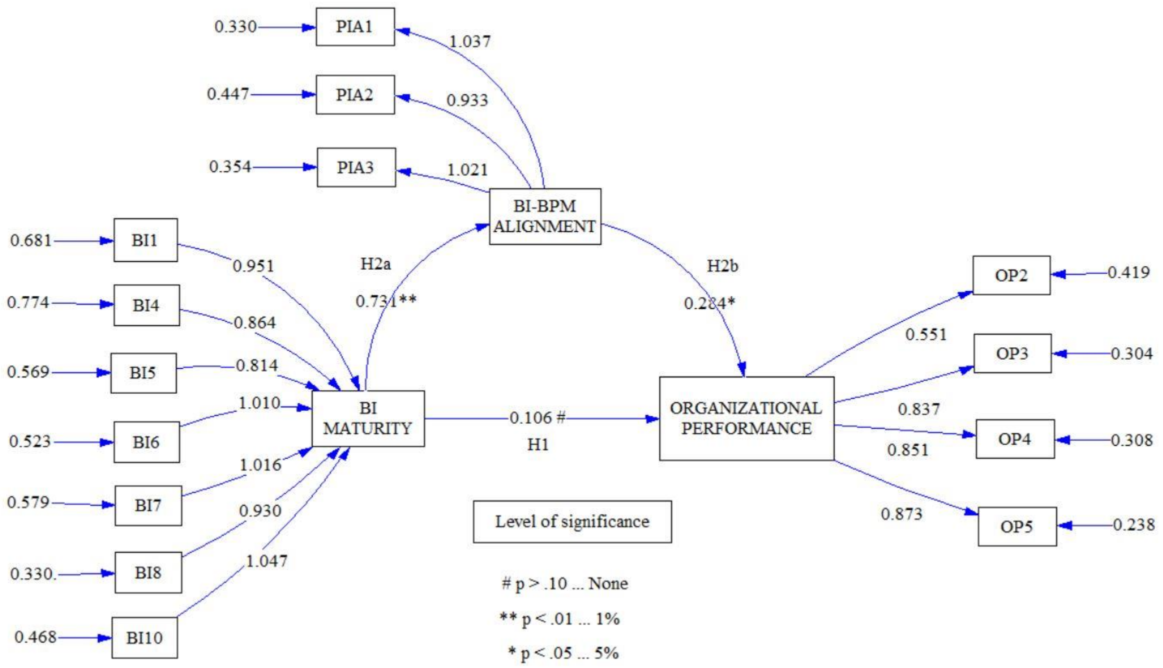

Figure III. Path diagram with path coefficients estimates and their significance levels

As Figure III reveals, the direct influence of BI maturity on organizational performance is positive (0.106), yet not statistically significant. On the other hand, the influence of BI maturity on BI-BPM alignment is also positive (0.731) and statistically significant at a 1% level of significance. Next, BI-BPM alignment positively influences (0.284) the organizational performance at a 5% level of significance. It may therefore be concluded that BI maturity positively influences organizational performance through BI-BPM alignment, but not directly.

To summarize, the data analysis and the presented results provide grounds for accepting or rejecting the hypotheses of this study. It may be concluded that the first hypothesis (H1), stating that *business intelligence maturity positively influences organizational performance* is rejected since the influence was revealed to be positive, but not statistically significant. Next, the second hypothesis (H2) was refined by way of two hypotheses: H2a indicating that *BI maturity positively influences BI-BPM alignment*, and H2b indicating that *BI-BPM alignment positively influences organizational performance.* The presented results confirmed both of these hypotheses. Therefore, it may be concluded that this research supports the second hypothesis (H2), namely that *the impact of BI maturity on Organizational performance is mediated by BI-BPM alignment.*

5. Discussion and conclusion

The results show that the impact of BI Maturity on Organizational performance is indirect and fully mediated by BI-BPM alignment, because hypothesis H2 is confirmed but H1 is not. This finding holds important theoretical and practical implications.

First, we developed and validated the construct of BI-BPM alignment utilized in the study. Although some dimensions of alignment between BI and BPM initiatives have already been discussed in the literature (Melchert et al., 2004; Hammer, 2007a; Hammer, 2007b; Marjanovic, 2007; Smart et al., 2009; Kohlbacher and Gruenwald, 2011; Blasini and Leist, 2013; Kohlbacher and Reijers, 2013; Wieland et al., 2015), none of those papers considered all of the dimensions of the alignment and its role as a mediator between BI maturity and organizational performance. The BI-BPM alignment construct that was developed builds on the mentioned research findings that stress the importance of different elements while aligning the two initiatives. It has three dimensions: coordination of BI and BPM initiatives, alignment of the BI and BPM terminology, and the use of BI to measure the process performance. The construct may also be used in future research.

Further, this study has also attempted to answer the question of how BI maturity affects organizational performance (Audzeyeva and Hudson, 2016; Popovič et al., 2012; Jaklič et al., 2018). The influence of BI on OP is usually analyzed through the BI value chain (Trieu, 2017), which represents the process of deriving value from information and information from data (Larson and Chang, 2016). Within the value chain, the crucial or necessary condition is business improvement or BI impacts, for which the effective use of high-quality information generated in BI processes is a prerequisite (Popovič et al. 2012; Trieu, 2017). Only decisions and actions provide business value and hence BI may be understood as an enabler, which makes it difficult to directly prove its business benefits (Larson and Chang, 2016).

Joint operations and the coordination of the two areas of BPM and BI can lead to BI being used for business process measurement and management. The improved operational efficiency of processes, such as higher staff productivity and lower operational costs, is recognized as one of the most vital potential BI impacts (Trieu, 2017; Popovič et al. 2012; Elbashir et al., 2008). In turn, business process improvements will usually translate into organizational performance improvements. A significant relationship between business process performance and organizational performance has been confirmed (Elbashir et al., 2008). Moreover, the use of BI can yield new products and services, in turn new processes with additional value.

BI-BPM alignment is not simply about the more effective use of the information generated in BI processes for the purposes of BPM. Instead, it can also assist in other parts of the BI value chain. The primary goal of BI is to provide high quality – in the broadest sense – information that supports smart decision-making. Researchers in this area generally agree that relevance, as a dimension of information quality, is particularly emphasized in the BI context (Grublješič and Jaklič, 2015a). Adequate relevance adds to its acceptance and the use of information generated in the BI conversion-and-use processes (Popovič et al., 2012). Therefore, as regards BI's impact on organizational performance, it may be considered to be very important. The problem of providing relevant information stems from the low structuredness of processes in which BI is chiefly used (i.e. management processes), making it difficult to identify information needs (Grublješič and Jaklič, 2015b). This problem is especially apparent if the focus of the BI initiative is on technology (Marjanovic, 2007).

Therefore, BPM can provide a framework for understanding which information is relevant for business improvement. Both BI and BPM share the same main goal of an improved organizational performance, but their starting points are different. For BI initiatives, it is information technology which is the starting point, and business opportunities are found afterwards. Yet, for BPM initiatives, the starting point is the improvement of the business processes. Measurement and monitoring are crucial for improving business processes and require adequate, i.e. relevant, information. In particular, the alignment of the initiatives can importantly contribute and further impact the organizational performance (Elbashir et al., 2008). This can be achieved if the BPM is strategically oriented and the measurement system of (especially key) business processes is appropriately defined, i.e. when key performance indicators have been properly identified (Popovič et al., 2012). From the aspect of the BI value chain, BI-BPM alignment can therefore also add to the quality of BI assets and is therefore again the path to ensuring that the BI holds greater value.

Our findings also hold implications for practice. Since integrated and aligned BI and BPM initiatives lead to better organizational performance, the results could encourage the managers of these two areas to improve their coordination. Moreover, our findings might encourage managers to give the BI initiative a more strategic role, an aspect which is currently largely overlooked (Dokhanchi and Nazemi, 2015). Like its strategic role, BI's capability to trigger efficient decisions to improve business processes is also underestimated (Olszak, 2016). Besides, the results might encourage BI teams to rely more on collaboration with BPM teams during the process of identifying the information needs.

The findings from the BI-BPM alignment construct development process can also be used for better understanding and bridging the gap between theory and practice. Business process management and organizational factors in general have long been recognized as an important success factor in the implementation and use of BI systems (Popovič et al., 2012; Grublješič and Jaklič, 2015a). The main reason for the frequently observed low level of alignment in practice is probably the fact that, as a rule, the development of BI systems starts principally as a technological initiative, while BPM is understood and implemented as a business (management) initiative. Thus, the gap between theory and practice in this field is merely a manifestation of the gap between the governance of IT and the rest of the business (Peppard and Ward, 1999; Peppard, 2001; Luftman, 2003). Therefore, it can be bridged by giving IT a more business and strategic role and by understanding that BI system development is primarily a business-focused and not IT-focused project. On the other hand, the gap could be narrowed by achieving a higher level of BPM maturity, especially in the direction of PPM. When BPM remains at the level of process modeling, i.e. at the operational level (McCormack et al., 2009; Hammer, 2007a; Kohlbacher and Gruenwald, 2011), project groups have no power to bring about the alignment. Further, in this matter, a more developed understanding of IT capabilities on the business side is required (Indihar Štemberger et al., 2011; Manfreda and Indihar Štemberger, 2019). In conclusion, we may state that to narrow the gap between theory and practice, above all education and awareness are needed on both the business and IT sides. The digital transformation movement is also bringing changes in this area since we are already realizing that management is increasingly involved in IT and better understands its role in business (Krotov, 2015; Dumeresque, 2014; Peppard, 2018), such that we can also expect improvements in BI-BPM alignment.

While these findings provide valid and generalizable results about the mediating role of BI-BPM alignment, they are accompanied by some limitations that provide a good basis for future research. The questionnaire was answered by one representative who answered on behalf of the

entire organization. Although this approach to data collection is common, there is a risk of biased perceptions. It might therefore be interesting to repeat the study by including more than one respondent from each organization.

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